Information Management Capability as Competitive Imperfection in the Strategic Factor Market of Big Data

Full Paper

Rafael Alfonso Brinkhues
Federal University of Rio Grande do Sul
rafael.brinkhues@caxias.ifrs.edu.br

José Carlos da Silva Freitas Junior
Federal University of Rio Grande do Sul
freitas.junior@ufrgs.br

Antonio Carlos Gastaud Maçada
Federal University of Rio Grande do Sul
acgmacada@ea.ufgrs.br

Abstract

The interest of the organizations in developing Big Data strategies is increasing significantly. However, the expectation of the value of these benefits and of the costs involved in acquiring or developing these solutions are not homogeneous for all of the firms, generating competitive imperfections in the market of strategic resources. Using Information Management Capability (IMC) as a premise to provide the required unique insight for Big Data strategies to be successful, this article proposes to analyze IMC as an imperfection agent in the market of strategic resources of Big Data. The formulated hypotheses were tested from a survey of 101 valid participants and analyzed with SEM-PLS. The results indicate a positive IMC influence on value expectation and a negative one on cost expectation. Cost expectation inversely affects the intent to purchase or develop the resources to implant Big Data strategies. Value expectation has a positive effect in both intents.

Keywords

Big data, strategic factor market, value expectation, cost expectation.

Introduction

"Big Data is possibly the most significant “tech” disruption in business and academic ecosystems since the meteoric rise of the Internet and the digital economy" (Agarwal and Vasant 2014, p.443). The interest of organizations in developing Big Data strategies is significantly increasing. From 2103 to 2014, the percentage of firms that already invest or plan on investing in Big Data –in the two subsequent years – grew from 64 percent to 73 percent (Gartner 2014). The volume of investments grows at an even greater rate. Big Data technology and services market will grow at a 26.4 percent Compound Annual Growth Rate (CAGR) to 41.5 billion dollars through 2018 (IDC 2014). The expected organizational impact is diverse, such as cost reduction, ascension of business insight, revelation of strategic information, and improvements in decision making (Kwon et al. 2014). However, the expected value of these benefits and the costs involved to acquire and develop these solutions are not homogeneous for every firm, generating competitive imperfections in the market of strategic resources.

According to the Strategic Factor Market Theory, to obtain superior performance, the firms need to be consistently more informed than the other firms that look to implement the same strategy (Barney 1986). The author affirms that analysis of the firm's capabilities can create these circumstances, more than analysis of the competitive environment. We believe that Information Management Capability (IMC) can bring the unique insight required so that Big Data strategies can be successful. We define IMC as the firm's set of skills that articulate information infrastructure, the architecture of information, and the access to information that makes organizational adjustment in response to the imposed changes from the internal and external environments possible. The literature indicates that IMC positively influences a firm's performance directly (Carmichael et al. 2011) or is mediated by other organizational capabilities (Mithas et al. 2011). There is no evidence that the firms' current IMC can accompany the sharp growth in the flow of unstructured data (White 2012).

However, that capability can carry out a relevant role in the expectation and intent of implementing a strategy to deal with Big Data. Many practitioners have been looking for opportunities due to easy access to computational capabilities and analytical software (Agarwal and Vasant 2014). On the other hand, 43 percent of the directors referred to budget deficits as the main barrier in delaying implementation of action to take advantage of this context (Mckendrick 2013). This evidences symmetry in the cost expectation of the resources for Big Data strategy. From an academic standpoint, much research has been looking into this phenomenon, especially in Information Systems (IS), analyzing value creation from these data (e.g. Brown et al., 2011; Davenport et al., 2012; Johnson, 2012; McAfee and Brynjolfsson 2012). Nevertheless, few works have focused on the relation between IMC and Big Data in order to obtain this value (Brinkhues et al. 2014; Mohanty et al. 2013). This paper aims to answer the following research question: How is the variation in the level of IMC among the organizations creating competitive imperfections in the resources market for implementation of Big Data strategies? To cover the research gaps, this paper proposes to build a measuring scale for IMC and conceptually develop a research model to evaluate empirically the relation between IMC and implementation of Big Data strategy. This model, based on Strategic Factor Market Theory, specifically investigates the influence of IMC on the value and cost expectations of the resources needed for this implementation and, based on the Transaction Cost Theory, the effect of these expectations on the intent of acquisition or development of these resources. The construction of the scale was carried out with basis on the literature and the use of data collection with executives via card sorting. The research model was tested through a survey with 101 directors utilizing SEM-PLS.

This article is organized as follows: the next section develops the hypotheses and presents the research model; the following section details the procedures in constructing the IMC scale and for data collection; the results are presented and discussed subsequently; and the final section presents conclusions and implications for research and managerial practice.

Information Management Capability and Strategic Factor Market

"Strategic Factor Market (SFM) are markets where the necessary resources for implementation of a strategy are acquired" (Barney 1986, p.1231). According to the author, firms can only extract superior performance when SFM is imperfect due to the differences in expectation of the future value of these strategic resources. In other words, it is necessary for the organizations to be able to exploit a larger value of the necessary resources for its strategic implementation rather than the costs in acquiring them being significantly smaller than their economic value. "The goal of big data programs should be to provide enough value to justify their continuation while exploring new capabilities and insights" (Mithas et al. 2013, p.18). To obtain this advantage, it is necessary for the firm to be consistently better informed than the other firms that are acting in the same SFM (Barney 1986). It is believed that IMC can serve as leverage in this advantage.

Mithas et al. (2011) coined the Information Management Capability construct to develop a conceptual model linking it with three other organizational capabilities (customer management, process management, and performance management). The results showed that these management capabilities mediate the positive influence of IMC on the performance of the firm. Mithas et al.'s IMC concept can be divided into three abilities: to provide data and information to users with appropriate levels of accuracy, timeliness, reliability, security, and confidentiality; to provide connectivity and universal access at an adequate scope and scale; and to adapt the infrastructure to the emerging needs and directions of the market. Carmichael et al. (2011) defined IMC as a second-order construct composed of compilation and production of information; access to information; and identification of information distribution requirements. Another author, Phadtare (2011), proposes that IMC are linked to five factors: acquisition and retention, processing and synthesis, recovery and use, transmission and dissemination, and support system and integration.

Based on the three aforementioned works (Mithas et al. 2011; Phadtare 2011; Carmichael et al. 2011), we identified five dimensions of IMC (access, distribution, people, architecture, and infrastructure). We then, as detailed in the next sections, performed a card sorting analysis with executives, which pointed to a grouping in three dimensions: access, architecture, and infrastructure. From this analysis, a definition for IMC was formulated and is applied in this work as corresponding to the firm's set of skills that articulate information infrastructure, the architecture of information, and access to information and enable organizational adjustment in response to changes imposed by internal and external environments. Thus, it is expected that organizations with more developed IMC are more accurate in expectations of value and can take advantage of the asymmetry of information in SFM from which competitive imperfections in SFM derive.

Additionally, it is expected that companies that have developed IMC in elevated levels in one of the previous eras of Information Management (IM) – Decision Support, Executive Support, Online Analytical Processing, Business Intelligence and Analytics (Davenport 2014) – have a greater value expectation of the next frontier: Big Data. This result is expected because development of IMC at an elevated level positively impacts organizational performance (Carmichael et al. 2011; Mithas et al. 2011), which favors the occurrence of a perceptive polarizing effect between past and present (Vasconcelos et al. 2006). In this manner, these firms would have a greater expectation of value extraction in strategies for Big Data, based on the positive experience they had with investments in IM in the past. Conversely, firms that have not reached the same level of IMC may not have had the same success in their investments in IM, and that negative experience may reflect in a greater cost expectation to implant this type of strategy.

H1: Firms with more elevated IMC have smaller cost expectation for implanting Big Data strategy.

H2: Firms with more elevated IMC have greater expectations of value extraction from implanting Big Data strategy.

Asymmetry in value expectation and the intent to purchase or develop the necessary capabilities for implanting BD strategy

Studies also evidence the positive effect of using data in the intent of acquiring Big Data solutions (Kwon et al. 2014). However, the resources and capabilities for implanting Big Data strategy can also be developed internally.

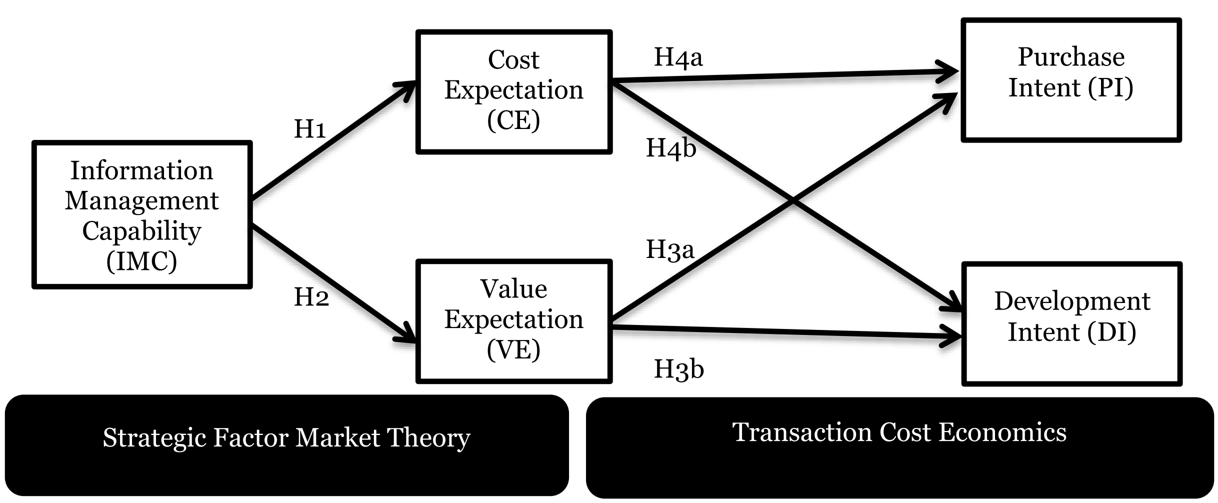

Figure 1. Research Model

The reason for the organizations' existence lies in realizing internal transactions more efficiently rather than looking in the market (Coase 1937). According to the economic approach of the organizations, the ones that do not arrange their resources in order to reach their objectives more efficiently than the market lose their reason to exist. Thereby, the search for the necessary resources to implant Big Data strategy can go down two paths: to develop them internally or to acquire them in the market. The organizations can internally develop the necessary capabilities for this implantation if they are efficient in rearranging the resources involved. However, if the cost to acquire such resources in the market is less than the cost to produce them internally, the organizations tend to acquire them.

Transactions costs are the consequence of the asymmetrical and incomplete distribution of information among the organizations involved in the exchange (Cordella 2006). The emergence of various suppliers with solutions for dealing with Big Data leaves uncertainty about which value can be exploited from these resources. So, the decision to buy or develop the necessary factors for implanting Big Data strategy is also affected by the differences in the asymmetrical expectations of value that can be extracted from this investment. It is expected that different levels of expectations positively influence both decisions, whether to purchase or internally develop the resources involved for value extraction of Big Data.

H3a: Firms with greater value extraction expectations of Big Data strategies present more elevated purchase intent of these solutions.

H3b: Firms with greater value extraction expectations of Big Data present more elevated intent to develop these solutions internally.

Asymmetry in cost expectation and intent to purchase or develop the necessary capabilities for implementing BD strategy

Some resources like MIPS (million of instruction per second) and terabytes storage for structured data are less expensive through Big Data technologies than through traditional technologies (Davenport 2014). However, the costs of other less tangible resources may be more difficult to predict.

For instance, frequently transaction costs increase when adopting an IS solution. However, these costs can be reduced when the costs associated with the adoption do not exceed the external costs that affect that adoption (Cordella 2006).

Just as it is expected to see companies with better developed IMC to have a reduced expectation of the costs necessary to employ Big Data strategy, it is also expected that this prediction of reduced costs favors a greater predisposition for this implementation. In addition, with a more exact cost expectation, because of the elevated level of IMC, companies can superintend a more adequate strategy into the budget. The inverse effect is also expected. Organizations with less developed IMC tend to have less exact cost predictions and therefore greater uncertainty when the time comes to decide whether to buy resources or develop them for Big Data strategy.

H4a: Firms with greater cost expectations for implanting Big Data strategies have less purchase intent for these solutions.

H4b: Firms with greater cost expectations for implanting Big Data strategies have less intent to develop these solutions internally.

Research Methodology

The test for the hypotheses was done utilizing least squares structural equation modeling (PLS-SEM) based on survey data. PLS-SEM is frequently recommended for research in Management since, in this field, oftentimes the data are not adherent to a multi-varied normal distribution and the models are complex and can still be formative. It is also recommended for less voluminous samples and for models with less explored technical support (Ringle et al. 2014; Hair et al. 2013). In light of the involved variables and the nature of this research, we consider the utilization of this statistical technique appropriate for empirically testing the hypotheses of the conceptual model.

However, a preliminary stage was realized beforehand with a survey and Card Sorting analysis to propose a measuring scale for IMC. This stage is detailed in the next section, followed by the steps with information on the sample, data collection, and validation.

Construction of the IMC Scale

A scale was constructed to measure IMC to be used in the quantitative phase through a survey. This scale was based on already existing research instruments (Carmichael 2011; Mithas et al. 2011). The need for constructing an IMC scale that could handle this new data environment did not influence the other variables, which already have tested scales.

For the scale, the Optimal Workshop tool was applied to perform a Card Sorting with ten IT executives. The data were collected from October 9, 2014, to October 23, 2014. Each online participant took an average of seven minutes to complete.

Based on the card sorting results, the scale could be reduced from 20 items in five dimensions (people, distribution, access, infrastructure, and information architecture) to ten items in three dimensions (distribution, infrastructure, and access), with the other two dimensions being absorbed by and permeating the three remaining ones. The reduction of items was made by analyzing the matrix where a cut above 60 percent of similarity was used. To evaluate the dimensions, we used the dendograms analysis for the best Merge Method, which often performs better than the Actual Agreement Method when the survey has fewer participants. It makes assumptions about larger clusters based on individual pair relationships (Optimal WorkShop, 2015). The scores of the cut represent 40 percent of the participants who agree with parts of this grouping.

The scales for the other variables of the research tool are adapted from the literature and modified as needed for this study. All items used a seven-point Likert scale (1-Strongly Disagree; 7 – Strongly Agree). A detailed description of these variables has been omitted due to the size limit for submission of this paper. Statistical analysis was made with support from the software SmartPLS version 3.2.0.

Sample Frame and Data Collection

Data were collected by making use of an online research form through the Google Forms platform. Collection was made from November 10, 2014, to December 16, 2014. Data were collected through social networks, especially through specific discussion groups about the addressed subjects. The notices were visualized by 29,282 people, clicked on by 208 people, and 114 completed forms were received. The answer rate was 59 percent. Among these, 13 were eliminated through three validation questions inserted in the questionnaire to help with quality control of the data, leaving us with a final sample of 101 forms. Thus, the sample exceeds the minimum of 68 cases, for a power of 0.8 and a medium effect size f2 of 0.15 (Hair et al. 2013) with the variables at a maximum number of two predictors. This minimum sample was calculated with support of the tool G*Power 3.1 (Faul et al. 2009).

Industry	%	Number of Employees	%	Annual Revenue	%
Technology	24%	Up to 50	27%	Up to 1 million dollars	16%
Manufacturing	18%	51 - 100	13%	1 to 6.7 million dollars	23%
Financial Services	12%	101 - 500	11%	6.7 to 37.5 million dollars	14%
Professional Services	11%	501 - 1,000	16%	37.5 to 125 million dollars	12%
Others	35%	More than 1,000	33%	More than 125 million dollars	36%

Table 1 – Respondent Firms Profiles (n=101)

Those who responded were managers and executives in IT or other areas related to the implantation of information management strategies. The profile of the respondent firms is summarized in Table 1, from which can be concluded that the sample is diversified and lightly focused on what is referred to as industry and size, whether through the number of personnel or invoicing. The two most apparent differences in the size variable appear in the first two rows. In the first row, there is a smaller percentage of invoicing up to one million dollars (16%) while the percentage of the number of companies with up to 50 employees is 27 percent. In contrast, the second row presents a greater percentage of invoicing (23% from 1 to 6.7 million dollars) and a smaller percentage of number of employees. A possible explanation for these differences may be in the high number of technological jobs, which have a high profitability potential, with a reduced number of employees. There were significant differences in the results relating to industry or firm size. In using Finite Mixture PLS, latent classes that evidence the presence of groups within a sample were not identified.

Results

Analysis of the results is first presented by an evaluation of the measuring model, followed by an evaluation of the structural model.

Evaluation of Measuring Model

The measuring model was evaluated through a series of reliability tests using composite reliability (CR), Cronbach's alpha, average variance extracted (AVE), and discriminant validity as indicated by Hair et al. (2013) and Ringle et al. (2014). As can be seen in Table 2, following the criteria of Fornell and Larcker (Henseler et al. 2009), the model converges and the result is satisfactory because AVE is above 0.50 for all of the variables.

Although the traditional indicator for evaluating internal consistency is Cronbach's alpha, composite reliability (CR) is the most adequate for PLS-PM because it is the least sensitive to the number of items in each construct (Ringle et al. 2014). In Table 2, it is also possible to observe that all the variables present both indicators (Cronbach's alpha and composite reliability) above 0.7. Therefore, all of the variable were considered to be adequate and satisfactory (Hair et al. 2013). Also presented in Table 2, the criteria of Fornell and Larcker (1981) were applied to verify the discriminating quality that shows the correlating values between the variables. It is possible to ascertain that there is no correlation between distinct variables greater than the square root of AVE of each variable – highlighted in gray in the main diagonal.

Variables	AVE	Composite Reliability	Cronbach's Alpha	CE	DI	IMC	PI	VE
Cost Expectation	0.778	0.875	0.715	0.882				
Develop Intent	0.698	0.874	0.784	-0.304	0.836			
IMC	0.548	0.923	0.907	-0.407	0.258	0.740		
Purchase Intend	0.657	0.851	0.747	-0.405	0.735	0.300	0.811	
Value Expectation	0.819	0.901	0.780	-0.392	0.318	0.647	0.360	0.905

Table 2 - Quality Criteria

As a last criterion for evaluating the quality of the measuring model, discriminant validity was calculated by utilizing the Cross Loadings analysis (Chin 1998). In the same way, as can be seen in Table 3, there are no indicators with factor loadings that are less elevated in their variable than in others. Having attended to the quality criteria and discriminant validity of the model, we will go on to the evaluation of the structural model in the next sub-section.

Items x Variables	IMC	CE	DI	PI	VE
IMC1	0.585	-0.178	0.022	0.004	0.363
IMC2	0.757	-0.255	0.236	0.263	0.459
IMC3	0.784	-0.273	0.177	0.165	0.543
IMC4	0.823	-0.347	0.319	0.351	0.656
IMC5	0.817	-0.289	0.190	0.203	0.600
IMC6	0.697	-0.182	0.033	-0.048	0.349
IMC7	0.735	-0.265	0.308	0.480	0.486
IMC8	0.686	-0.293	0.107	0.286	0.425
IMC9	0.711	-0.417	0.125	0.191	0.337
IMC10	0.773	-0.455	0.259	0.186	0.452
CE1	-0.387	0.885	-0.299	-0.316	-0.390
CE2	-0.331	0.879	-0.237	-0.399	-0.301
DI1	0.253	-0.285	0.826	0.819	0.305
DI2	0.239	-0.204	0.892	0.588	0.253
DI3	0.145	-0.261	0.786	0.385	0.226
PI1	0.253	-0.285	0.826	0.819	0.305
PI2	0.249	-0.404	0.481	0.858	0.362
PI3	0.229	-0.269	0.517	0.751	0.166
VE1	0.557	-0.361	0.325	0.362	0.907
VE2	0.615	-0.349	0.250	0.289	0.903

Table 3 – Cross-Loadings

Evaluation of the structural model

To test the hypotheses and the predictive power of the model, Pearson's coefficients of determination (R2), the effect size (f2), predictive validity (Q2), and path coefficient (r) were calculated. According to the criteria of Cohen (1988), we can verify a medium effect of the model on the Cost Expectation (0.166) and Develop Intent (0.139) variables, a large effect on the Value Expectation (0.419) variable, and an almost large effect on the Purchase Intent (0.212) variable.

The Bootstrapping analysis with 1,000 samples demonstrates that all the relations of the observable variables with the latent variables, and among the latent variables, have significant correlations and coefficients of regression at $p<0.001$, rejecting Ho. Two other quality evaluations of the model adjustment, the predictive validity (Q2), and the effect size (f2) were then performed through the Blindfolding procedure. Table 4 shows that all the Q2 are above zero, demonstrating the model's accuracy. Analysis of the effect size considers a medium utility of CE, DI, and PI for adjustment of the model and close to an almost large utility of VE, according to the criteria considered by Hair et al. (2013).

Variables	R^2	Q^2	f^2
CE	0.166	0.112	0.189
DI	0.139	0.085	0.143
PI	0.212	0.111	0.119
VE	0.419	0.333	0.339

Table 4 – Results of R^2, Q^2 and f^2

Finally, the path coefficients, illustrated in Figure 2, show that all the hypotheses have been supported. A discussion of these results is presented in the next section.

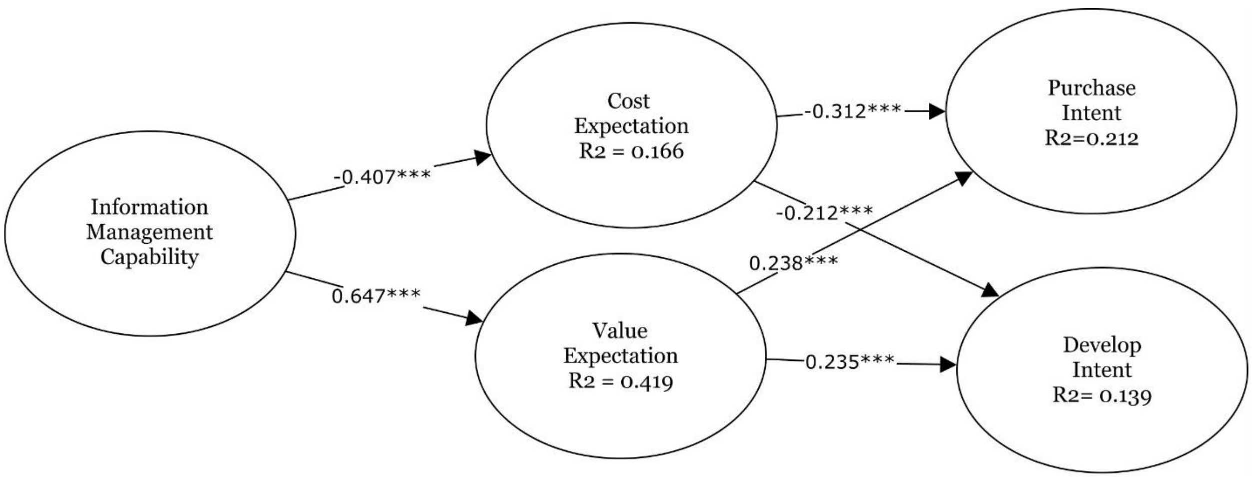

Figure 2 – Results of Empirical Model: Path Coefficients and R^2

* p<.05; ** p<.01; *** p<0.001

Discussion and Implications

Contributions to Research

This paper brings some contributions to the literature in Management Information Systems by exploring a relatively recent theme (Big Data) and its relation to a capability previously developed by the firm (IMC). Specifically, we looked to understand and analyze this phenomenon by focusing on its impact on the organizations. "This focus creates a tighter linkage between data and business models: we care deeply about business transformation and value creation through data, and less for algorithms or frameworks without a linkage to business value" (Agarwal and Vasant 2014, p.445).

Firstly, the research applied a rarely used theory in IS – Strategic Factors Market. This theory supported the development of the hypotheses – along with the Transaction Cost Theory (widely used in IS) – confirmed in the statistical analysis. With this theoretical foundation and from the indications found in the literature, it was possible to establish Hypothesis 1. Our results attest that IMC can have a negative impact on the cost expectation of the necessary resources for implanting Big Data strategy. These results confirm that the organizations have different cost expectations in the search for strategic resources (Barney 1986). IMC plays a relevant role in this heterogeneity of perceptions, whether through more accuracy (Mithas et al. 2011) in access to and distribution of information or through the perceptive polarization effect (Vasconcelos et al. 2006). Companies that were not successfully able to develop IMC may have a more elevated cost expectation for implanting a new strategy related to information management. However, this effect appears to be more strongly evident in the relation exposed in Hypothesis 2. It was demonstrated that IMC positively impacts the expectation of value extraction that can be extracted from Big Data strategy. This was the most elevated effect found in the research, which may indicate a product of the developed abilities or a reflex of successful experiences with information management.

On the other hand, the impact of the cost expectation on the intent of purchase or development of resources and capabilities to implant a strategy to deal with voluminous and heterogeneous data was explained in Hypotheses 3 – H3a (purchase) and H3b (develop). This relation of negative impact was supported by empirical data that demonstrated that a high cost expectation impacts even more negatively on purchase intent than on the intent to internally develop the resources and capabilities necessary for the strategy. Conversely, Hypotheses 4 (H4a and H4b) were supported by the research showing that a greater expectation of future value extraction positively impacts the intent to purchase or develop Big Data strategies. In this case, the evidenced size effects for purchase or development of the required resources for these strategies were very similar. Nevertheless, this is not to evaluate whether or not these expectations correspond to market reality. It is important to note that, in general, investments in IS strategies only reduce transaction costs if there are fewer resources consumed than economy generated (Ciborra 1996).

Through two theoretical perspectives, our research contributes to comprehending the impact that the IMC already developed in the organizations may have on the adoption or non-adoption of new strategies in response to changes in the area of information. More importantly, the study reveals the role of this capability as a potential source of imperfections in the strategic factor market and may be a first step in investigating IMC's role in the competitive performance of the firms.

In addition, alongside the points of view from IMC literature, we propose a new definition that is more in tune with the current context and the information management needs of the organizations. We even projected and validated a new scale for measuring this construct.

Implications for Practice

The implications of this study on practice can be classified for two types of organizations: the organizations that look for a solution to respond to environmental changes caused by Big Data and the organizations that offer these solutions. For the companies that are planning to implant Big Data strategies, the results reveal that there is a large variation in expectation for both value and cost of the needed resources. This variation may reflect opportunities to search the market for underestimated resources or to incur the risk of acquiring overvalued resources. To reduce these risks and improve performance in the search to exploit these opportunities, this research shows that investing in information management not only improves organizational performance (Carmichael et al. 2011; Mithas et al. 2011), it may also contribute in evaluating future strategies.

From the other side of market, this work may serve the organizations that offer the resources and capabilities to implant Big Data strategies some insight into the expectations of their current or potential consumers. Understanding the differences in perception of the organizations with different levels of IMC may contribute in creating a more adequate solution as well as to the success of that solution in IMC development in greater levels for their clients.

Limitations and Future Research

The sample of the study was very heterogeneous, as can be noted in Table 1, for having collected data non-systematically and may not reflect the population of the organizations in its entirety. It is also not possible to identify if the results apply to a specific group of organizations. The purchase expectation and cost expectation constructs were measured using only two indicators, and even though both presented good performance in validity and reliability, there is still one indicator less than recommended.

This research opens the way for new investigations in IS, particularly in what relates to IMC, the context of Big Data, and even for new studies making use of the SFM Theory. Regarding IMC, we believe that future research may strengthen the strategic role of these capabilities, especially in this Big Data context. As for

SFM, it can be utilized to analyze other phenomena in the area as well as articulated with other theories spread throughout IS literature. The model could hold true for IS strategy in general and can be investigated with other technologies (such as business analytic or business intelligence).

Conclusion

This study, despite bringing in quantitative results, is exploratory given the nature of the content analyzed. We wanted to inspect how organizations with IMC previously developed by the organizations affected the expectations and intent of these firms in superintending in one new strategy for information management.

Our results offer perceptions about the effect on the relations between IMC and cost and future value expectation in addition to the effect of these expectations on the intent to purchase or develop the needed resources for implanting Big Data strategy. Generally, the results unveiled that IMC positively influences value expectation and negatively influences cost expectation. Value expectation homogeneously and positively impacts the intent to purchase or develop these resources. Finally, cost expectation negatively influences development intent and, even more sharply, purchase intent of the resources and capabilities for Big Data.

If one key resource for survival in this new environment is the ability to obtain access to more information and to be able to manage this information flow (Cordella 2006), this research contributes to IS literature for exploring the potential of IMC in this Big Data context. From an academic standpoint, this study tested a less diffused theory in the area's literature and can be explored more to analyze IS themes. Lastly, the research provides for companies that supply Big Data solutions and, mainly, for the organizations that intend to invest in strategies to deal with this change in the information environment.

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Appendix A. Information Management Capability Scale

IMC1 – The firm has systems to gather and integrally deal with all information on the company’s own processes.

IMC2 – The firm has efficient systems for gathering and dealing with information in the competitive environment.

IMC3 – The firm’s employees* have rapid, trouble-free access to the information and knowledge they need.

IMC4 – The firm has a clear system to distribute information to employees, customers, and suppliers in accordance with detected needs.

IMC5 – In my firm, there are mechanisms in place that provide employees with incentive to share information.

IMC6 – The firm's processes ensure appropriate levels of information’s reliability, accuracy, timeliness, security, and confidentiality.

IMC7 – The mechanisms for providing data and information are updated according to the needs and directions of the business.

IMC8 – The information is integrated from all sources to support the organization's processes.

IMC9 – The information is integrated from all sources to support organizational decision making.

IMC10 – Information on satisfaction and customer dissatisfaction are used for process improvement. The formulated hypotheses were tested from a survey of 101 valid participants and analyzed with SEM-PLS.